Development of Intelligent Remote Sensing Payloads for CubeSat Applications

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Abstract

The paper describes the development of a remote sensing payload for CubeSat applications. The inclusion of artificial intelligence into remote sensing payload has been pursued in the IRIS (Intelligent Remote sensing and Internet Satellite) and Lilium CubeSat programs. The paper discusses the development of a series of intelligent remote sensing payloads for CubeSats to address the limitations on computational resources, power, and communication bandwidth. From 2018 to 2021, under the IRIS program, an optical remote sensing payload that contains a high focal-length telescope, a CMOS detector, and the data operation board was developed. An edge intelligence for landslide detection and cloud segmentation is investigated by using MobileNet V2 network. The design has been implemented and tested by using an airborne platform. The design is further refined in the Lilium program with enhanced resolution and frame rate. Functions including auto-focus, automatic white balance, and gain control are also realized in the payload. To account for low-illumination scenario, a zero DCE (zero reference deep curve estimation) is utilized. Further, a light-weight U-net is implemented in the FPGA to achieve cloud detection and segmentation and a YOLO-SPD is implemented for object detection. This self-developed payload has been prototyped and is under tests. The payload will be integrated into the 6U Lilium-2 CubeSat and is planned to be launched in 2025.

1 INTRODUCTION

The Cube satellites (CubeSats) have enabled many different space applications and promoted the development of space industry. Many universities, research organizations, and companies have adopted CubeSats for training, technology demonstration, and commercial applications to take advantage of CubeSats in terms of the use of miniaturized components and the standardized process in satellite development [1,2,3]. In the paper, the endeavor that is led by the National Cheng Kung University (NCKU) is discussed with the emphasis on the development and verification of the intelligent remote sensing payload.

For remote sensing applications, cubesats are constrained as the spatial resolution cannot be significantly improved to be compatible with instruments in micro or larger satellites. However, due to the low cost and short development time, the satellites can be deployed as a constellation so that the temporal resolution by using cubesats have been effectively achieved by some remote sensing constellations such as Planet [4]. The high revisit frequency may be valuable in disaster monitoring and mitigation. With the advance of deep learning technologies, it is also anticipated that the augmentation of artificial intelligence into remote sensing payload onboard the cubesat can enhance the mission effectiveness. The learning capability can be used to segment clouds so that only valuable data are transmitted. Further, the learning capability can be used to detect targets in near real time so that useful images can be better accumulated. The artificial intelligence capability can be realized by using high computation power embedded processor and is being pursued by different organizations [5,6,7]. The paper describes the development of a remote sensing payload for CubeSat applications. The payload is developed by inclusion of artificial intelligence and is realized in the IRIS (Intelligent Remote sensing and Internet Satellite) and Lilium CubeSat programs.

The paper is organized as follows. In Section 2, the cubesat missions that have been carried out by the NCKU team will be discussed. In Section 3, the development of intelligent remote sensing payloads for cubesats are presented. Some flight results are then presented in Section 4. Finally, concluding remarks are made in Section 5.

2. CUBESAT MISSIONS

The National Cheng Kung University (NCKU) Space laboratory has been responsible for several cubesat projects with the goal of setting up a sustainable infrastructure for the advance of key enabling cubesat technologies and incubate highly motivated talents in space engineering through the development including the design, analysis, manufacturing, assembly, integration, test, launch and operation of cubesats. Figure 1 depicts the development of cubesats of the laboratory [8]. The PACE (Platform for Attitude Control Experiment) cubesat was developed since 2002 and the cubesat was launched in 2014 [9]. The laboratory participated in the European QB50 program to facilitate the PHOENIX cubesat for insitu measurements of the lower atmosphere. PHOENIX was launched in 2017 and has operated for approximately two years before reentry [10]. The IRIS project was conducted in the period of 2018-2021 under the support of the Ministry of Science and Technology, Taiwan. The objective of IRIS project is to design, develop, launch, and operate CubeSats in low earth orbit for technology demonstration. The mission objective of the IRIS-A is to demonstrate Internet of Things (IoT) communication technology in low earth orbit. The IRIS-A cubesat was launched in 2022 and is still operating. The IRIS program also designed the IRIS-B cubesat to perform smart remote sensing mission. The bus system of the IRIS-B shares a lot of commonalities with the IRIS-A even though the mission is drastically different. To echo the recent trends on artificial intelligence and deep learning, the objective is to design a smart remote sensing payload to detect in-situ landslide objects and debris flow. Such a mission is deemed important in disaster mitigation. Based on the platform of the IRIS, the IRIS-C cubesat has also been designed, manufactured, and launched in 2023.

Based on the results of the IRIS program, the team proceeds to conduct Lilium project under the support of the National Science and Technology Council, Taiwan. The lilium project aims to develop key enabling technologies for cubesats. To this end, the project encompasses the investigation of Ku-band communication and smart remote sensing payloads and electric propulsion and deployment mechanism experiments. It is anticipated that the development of these key technologies together with the mature cubesat platform technologies can be integrated to enhance the overall system level technology readiness level.

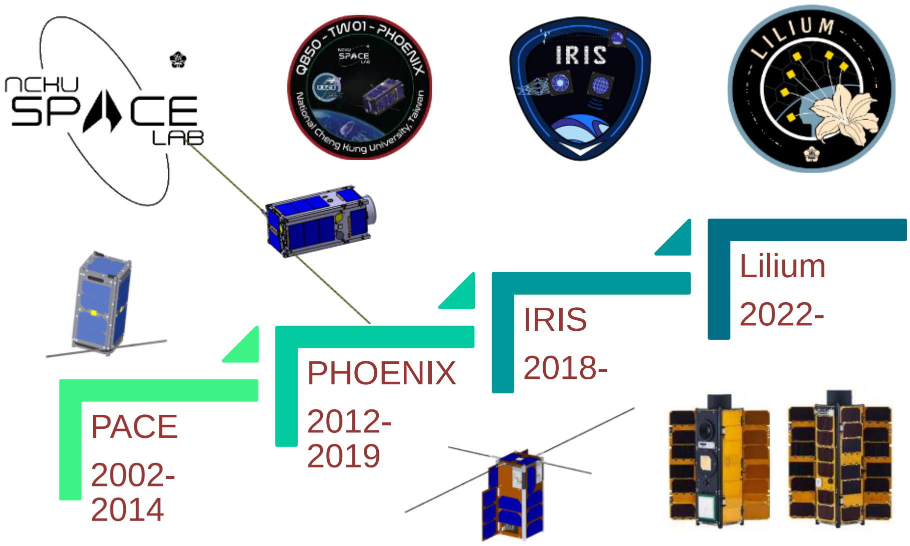

Figure 1. NCKU CubeSats.

3. REMOTE SENSING PAYLOAD AND RELEVANT TECHNOLOGIES

Even though some cubesat constellations have been deployed to facilitate remote sensing data, it is recognized that due to the limitations on physical size and communication bandwidth, the remote sensing payload of cubesats may be different from those of large satellites. The three goals setup in the key technology development are

1. Smart
2. Small
3. Low power

Figure 2 depicts the schematic diagram of the remote sensing payload of the IRIS cubesat. The payload includes a lens, an image acquisition unit, processing unit, and interface unit. The acquisition unit contains a high-resolution CMOS sensor (1920 x 1200 pixels) and image data capture board. The processing is realized by the image data operation board in which processing units are provided to realize image processing and recognition tasks. In addition, a communication board is used to serve as the interface to the on-board computer of the cubesat. Figure 3 further illustrates the interface arrangement between the payload and IRIS bus.

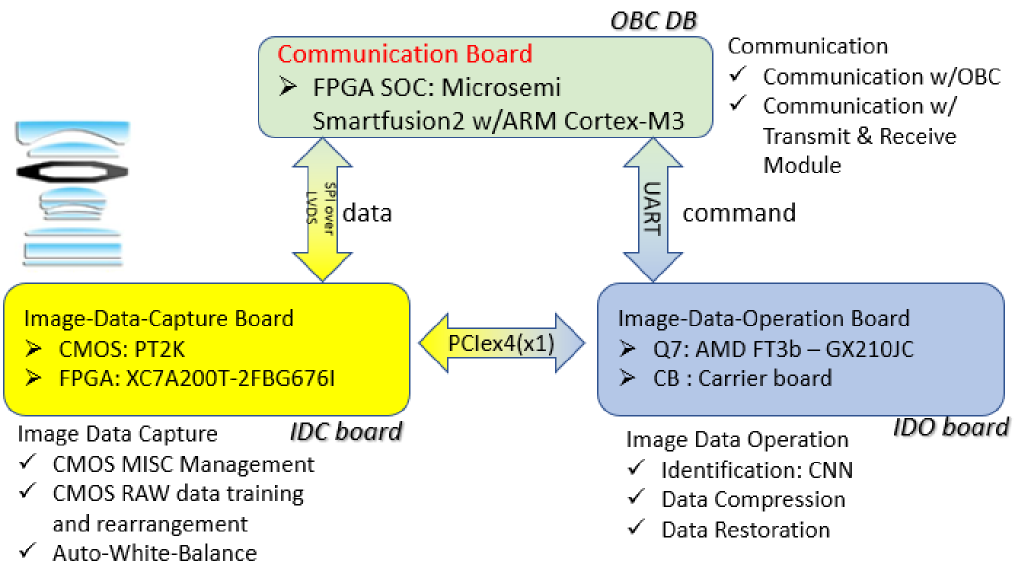

Figure 2. Smart remote sensing payload of the IRIS cubesat.

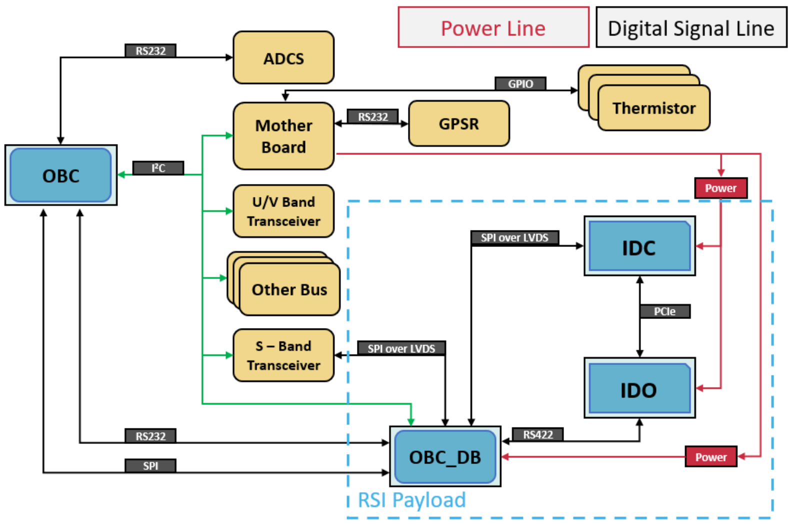

Figure 3. Interface between the payload and cubesat.

Key to the development of the remote sensing payload is the processing capabilities. In the IRIS project, the objective is to develop the smart remote sensing payload for near-real-time debris flow and landslide object detection. To this end, extensive work is conducted in the ground segment to train a neural network model that is capable of detecting debris flow and landslide object. Figure 3 depicts the training and inference procedures. Existing remote sensing image data in the interested region in Taiwan are collected and labelled to constitute a set of data that is amenable for the training of a convolutional neural network. An edge intelligence for landslide detection and cloud segmentation is investigated by using MobileNet V2 network. The design has been implemented and tested by using an airborne platform. A key step in the training and operation of the neural networks is the adoption of bi-dimensional empirical mode decomposition (BEMD) algorithm to enhance the task of feature extraction and object classification. The Hilbert-Huang transform (HHT) is a generation of the classical

Hilbert transform by introducing the empirical mode decomposition (EMD) to process mono-dimensional signal. The BEMD is a generalization of EMD in an attempt to extract features at multiple scales or spatial frequencies [11,12]. Under this framework, the features or intrinsic mode functions (IMF) are extracted by sifting processing. To simplify the operation the hue channel which can be obtained through a conversion from the RGB data of the image is retained for feature extraction and object detection. By using the BEMD feature extraction schemes, the convolution neural network can be more easily trained and the inference by using the network does not require a significant amount of computation nor power resources.

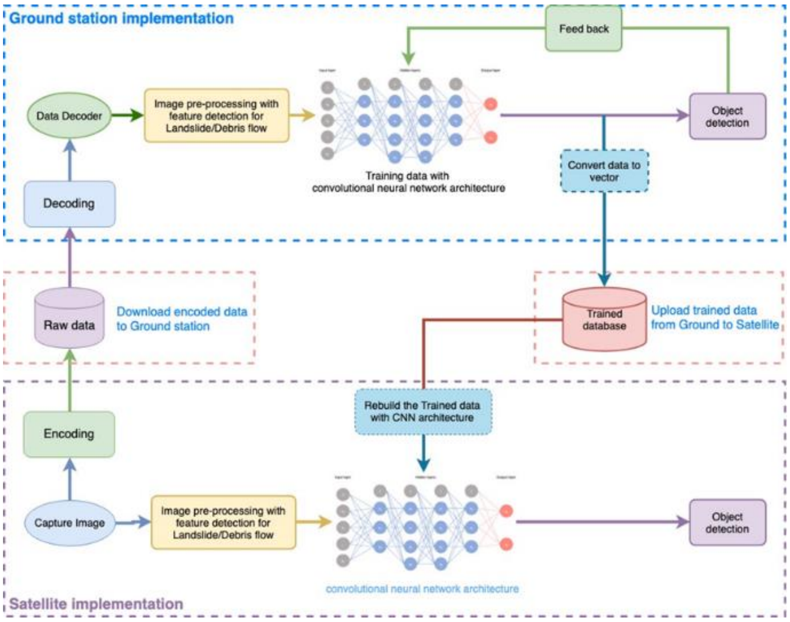

Figure 4. Training and interference in the IRIS payload development.

The remote sensing payload of the Lilium project is an advanced design. It contains a lens, focal plane array, and processing unit. The main differences are

1. A reflective lens is designed to enhance the resolution.
2. The CMOS sensor is upgraded to achieve 4096 x 3072 pixels.
3. The total power is reduced.
4. Additional deep learning algorithms are developed.
5. Radiation tests are performed.

In the meantime, the Lilium cubesat is upgraded to be of 6UXL form factor to accommodate the payload. Figure 5 depicts the training for cloud segmentation and ship detection. The configuration of the Lilium-2 cubesat for the verification of the remote sensing payload performance is shown in Figure 6.

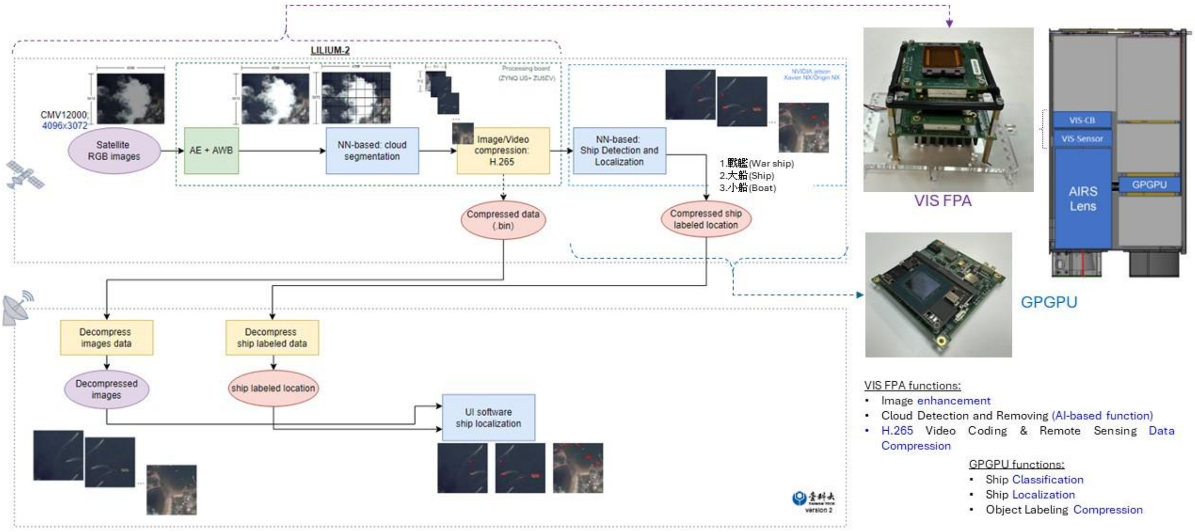

Figure 5. Training and inference in the Lilium-2 remote sensing payload.

Figure 6. Lilium-2 cubesat.

The cloud segmentation will be investigated in the Lilium-2 remote sensing payload. The cloud segmentation In the past, the use of machine learning and deep leaning for cloud detection and segmentation have been investigated in satellite image analysis [13-17]. In [18], a three-stage method is proposed for thick cloud removal and ground information reconstruction in which U-Net is used for segmentation [19,20] and cGAN is used for reconstruction [21-23]. To facilitate the development, synthetic data together with true remote sensing data are used. It is shown that the proposed method leads to improved performance [18]. In addition, several acceleration techniques including zero DCE (zero reference deep curve estimation), quantized convolution, and piecewise approximation are implemented to enhance the performance of the edge computer. Further, a light-weight U-net is implemented in the FPGA to achieve cloud detection and segmentation and a YOLO-SPD is implemented for object detection.

3. FLIGHT RESULTS

The Lilium-1 cubesat was launched on December 1st, 2023. The satellite has then stabilized is commissioned to perform experiments of payloads. The Lilium-1 is equipped with the remote sensing payload that was developed in the IRIS project with some refinements. Figure 7 depicts the Lilim-1 cubesat and its remote sensing payload. Figure 8 depicts a picture that is acquired when the satellite is over the southern part of Taiwan. A sequence of pictures is indeed obtained for the verification of the positioning, attitude control, and payload capabilities. A snapshot is depicted in Figure 9 in which a series of photos are obtained when the satellite is over Taiwan. This implies that the major satellite and payload functions operate as expected.

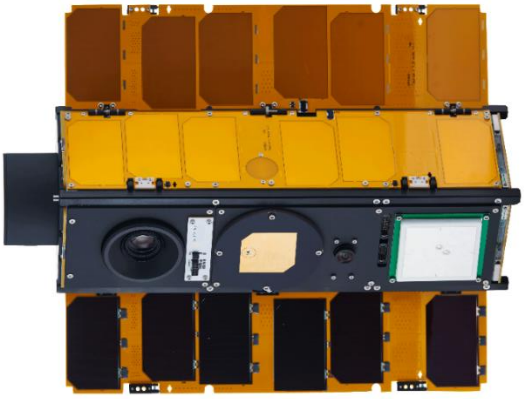

Figure 7. Lilium-1 cubesat.

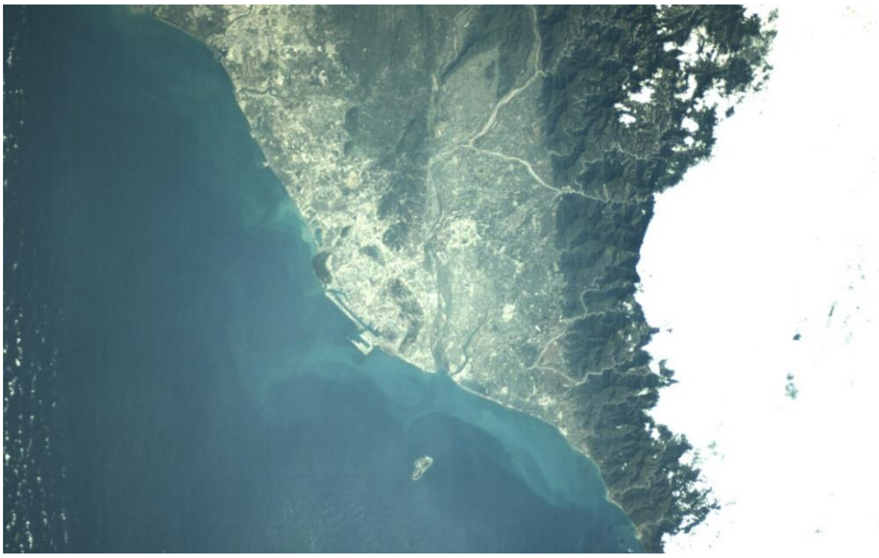

Figure 8. Photo taken by Lilium-1.

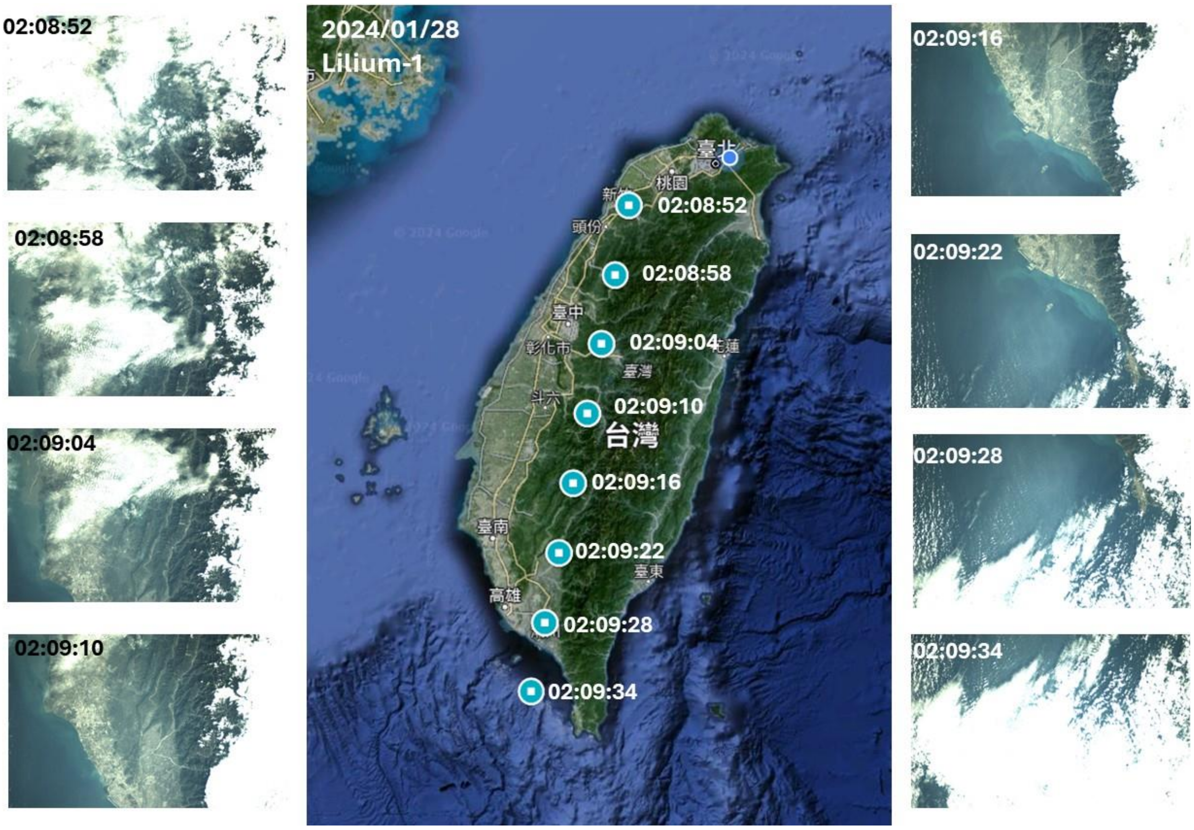

Figure 9. A series of photos taken by Lilium-1.

By using the remote sensing payload, the cubesat has acquired and downloaded some photos for the verification of the payload and training of neural networks. Figure 10 depicts the development of cloud detection network and its application to the aforementioned photo. The clouds are apparently detected.

5. CONCLUDING REMARKS

The paper describes the development of a remote sensing payload for CubeSat applications. The evolution of the payload and the inclusion of artificial intelligence has been discussed. It is anticipated that the fusion of miniaturized payload, intelligent processing, and low power design may enable cubesat-based remote sensing missions. This self-developed payload has been prototyped and is under tests. The payload will be integrated into the 6U Lilium-2 CubeSat and is planned to be launched in 2025.

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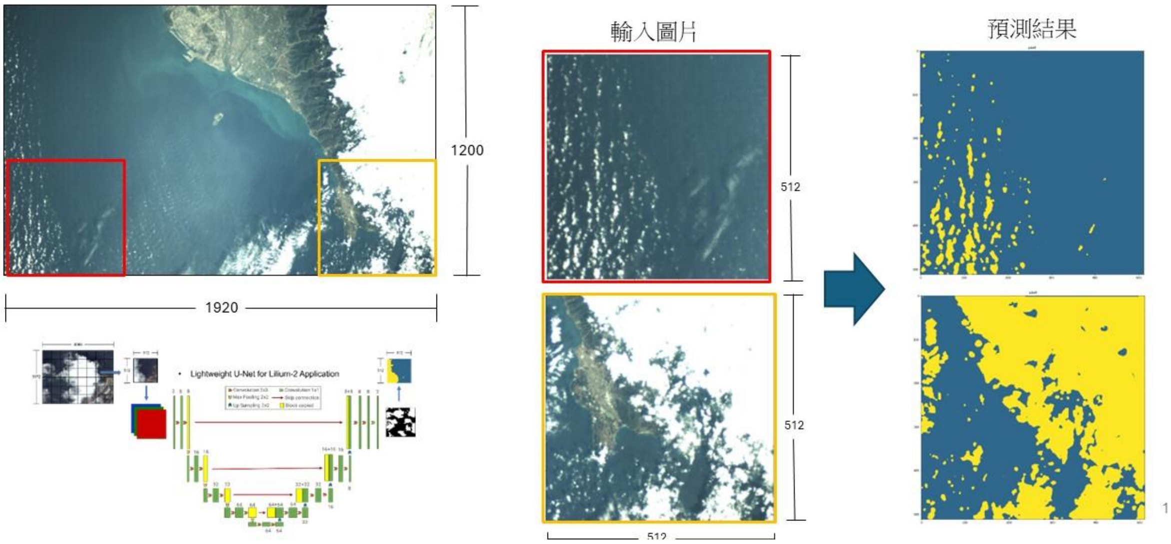

Figure 10. Cloud detection results.

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